Simplifying Decision Tree Interpretability with Python & Scikit-learn

Tags: Decision Trees, Interpretability, Python, scikit-learn

This post will look at a few different ways of attempting to simplify decision tree representation and, ultimately, interpretability. All code is in Python, with Scikit-learn being used for the decision tree modeling.

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When discussing classifiers, decision trees are often thought of as easily interpretable models when compared to numerous more complex classifiers, especially those of the blackbox variety. And this is generally true.

This is **especially** true of rather comparatively simple models created from simple data. This is much-less true of complex decision trees crafted from large amounts of (high-dimensional) data. Even otherwise straightforward decision trees which are of great depth and/or breadth, consisting of heavy branching, can be difficult to trace.

Concise, textual representations of decision trees can often nicely summarize decision tree models. Additionally, certain textual representations can have further use beyond their summary capabilities. For example, automatically generating functions with the ability to classify future data by passing instances to such functions may be of use in particular scenarios. But let's not get off course -- interpretability is the goal of what we are discussing here.

This post will look at a few different ways of attempting to simplify decision tree representation and, ultimately, interpretability. All code is in Python, with Scikit-learn being used for the decision tree modeling.

Building a Classifier

First off, let's use my favorite dataset to build a simple decision tree in Python using Scikit-learn's decision tree classifier, specifying information gain as the criterion and otherwise using defaults. Since we aren't concerned with classifying unseen instances in this post, we won't bother with splitting our data, and instead just construct a classifier using the dataset in its entirety.

```
import numpy as np
from sklearn import datasets
from sklearn import tree

# Load iris
iris = datasets.load_iris()
X = iris.data
y = iris.target

# Build decision tree classifier
dt = tree.DecisionTreeClassifier(criterion='entropy')
dt.fit(X, y)
```

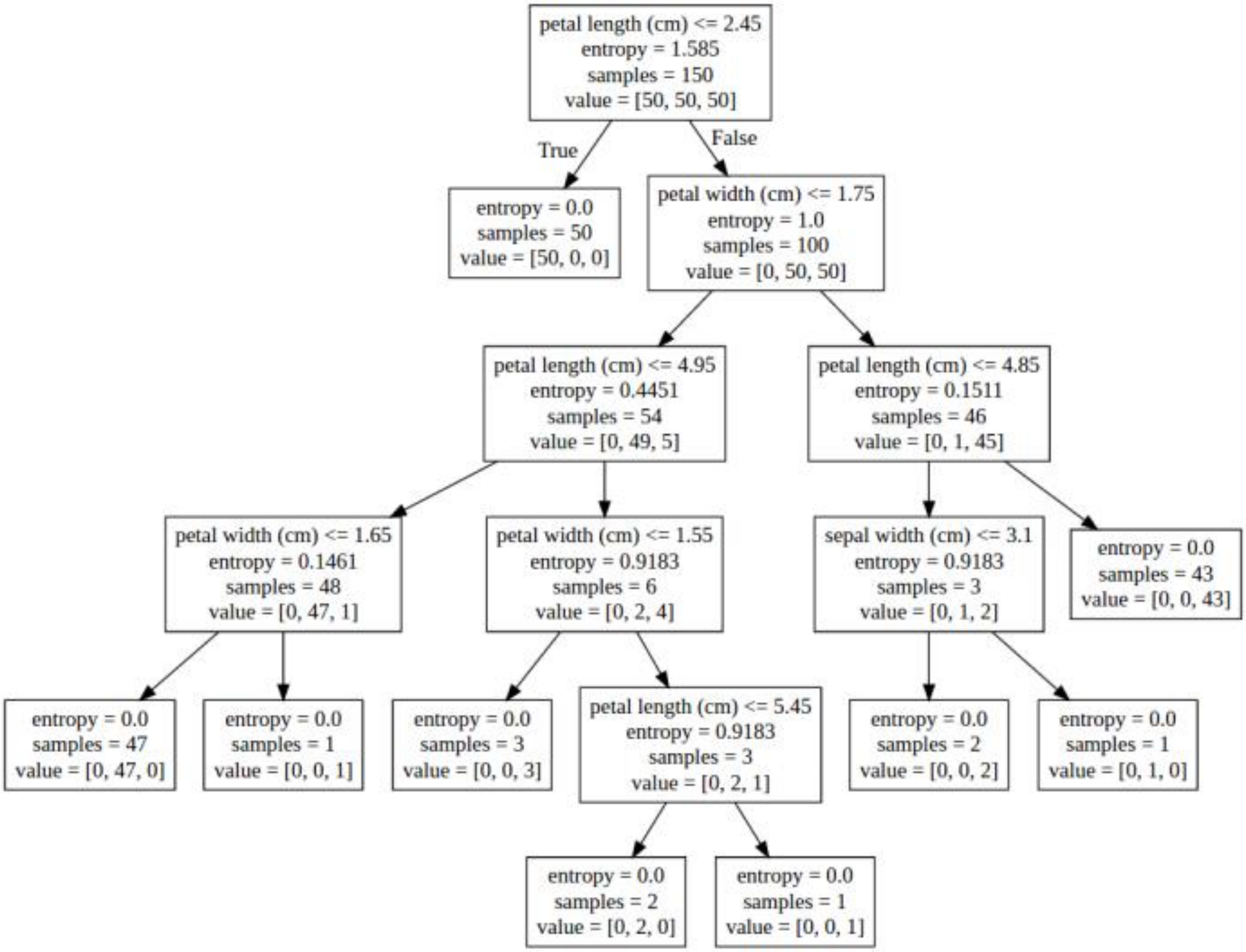
dt-hacks-1.py hosted with ❤ by GitHub view raw

One of the easiest ways to interpret a decision tree is visually, accomplished with Scikit-learn using these few lines of code:

```
dotfile = open("dt.dot", 'w')
tree.export_graphviz(dt, out_file=dotfile, feature_names=iris.feature_names)
dotfile.close()
```

dt-hacks-2.py hosted with ❤ by **GitHub** view raw

Copying the contents of the created file ('dt.dot' in our example) to a [graphviz rendering agent](), we get the following representation of our decision tree:



Representing the Model as a Function

As stated in the outset of this post, we will look at a couple of different ways for textually representing decision trees.

The first is representing the decision tree model [as a function]().

```
from sklearn.tree import _tree

def tree_to_code(tree, feature_names):

        '''
        Outputs a decision tree model as a Python function

        Parameters:
        -----------
        tree: decision tree model
                The decision tree to represent as a function
```

```
		feature_names: list
			The feature names of the dataset used for building the decision tree
		'''

		tree_ = tree.tree_
		feature_name = [
			feature_names[i] if i != _tree.TREE_UNDEFINED else "undefined!"
			for i in tree_.feature
		]
		print "def tree({}):".format(", ".join(feature_names))

		def recurse(node, depth):
			indent = "  " * depth
			if tree_.feature[node] != _tree.TREE_UNDEFINED:
				name = feature_name[node]
				threshold = tree_.threshold[node]
				print "{}if {} <= {}:".format(indent, name, threshold)
				recurse(tree_.children_left[node], depth + 1)
				print "{}else:  # if {} > {}".format(indent, name, threshold)
				recurse(tree_.children_right[node], depth + 1)
			else:
				print "{}return {}".format(indent, tree_.value[node])

		recurse(0, 1)
```

dt-hacks-3.py hosted with ❤ by GitHub view raw

Let's call this function and see the results:

```
tree_to_code(dt, list(iris.feature_names))
```

```
def tree(sepal length (cm), sepal width (cm), petal length (cm), petal width (cm)):
  if petal length (cm) <= 2.45000004768:
    return [[ 50.   0.   0.]]
  else:  # if petal length (cm) > 2.45000004768
    if petal width (cm) <= 1.75:
      if petal length (cm) <= 4.94999980927:
        if petal width (cm) <= 1.65000009537:
          return [[  0.  47.   0.]]
        else:  # if petal width (cm) > 1.65000009537
          return [[ 0.  0.  1.]]
      else:  # if petal length (cm) > 4.94999980927
        if petal width (cm) <= 1.54999995232:
          return [[ 0.  0.  3.]]
        else:  # if petal width (cm) > 1.54999995232
          if petal length (cm) <= 5.44999980927:
            return [[ 0.  2.  0.]]
          else:  # if petal length (cm) > 5.44999980927
            return [[ 0.  0.  1.]]
    else:  # if petal width (cm) > 1.75
      if petal length (cm) <= 4.85000038147:
        if sepal length (cm) <= 5.94999980927:
          return [[ 0.  1.  0.]]
        else:  # if sepal length (cm) > 5.94999980927
          return [[ 0.  0.  2.]]
      else:  # if petal length (cm) > 4.85000038147
        return [[  0.   0.  43.]]
```

Interesting. Let's see if we can improve interpretability by stripping away some of the "functionality," provided it is not required.

Representing the Model as Pseudocode

Next, [a slight reworking of the above code] results in the promised goal of this post's title: a set of decision rules for representing a decision tree, in slightly less-Pythony pseudocode.

```
def tree_to_pseudo(tree, feature_names):

	'''
	Outputs a decision tree model as if/then pseudocode

	Parameters:
	-----------
	tree: decision tree model
		The decision tree to represent as pseudocode
	feature_names: list
		The feature names of the dataset used for building the decision tree
	'''

	left = tree.tree_.children_left
	right = tree.tree_.children_right
	threshold = tree.tree_.threshold
	features = [feature_names[i] for i in tree.tree_.feature]
	value = tree.tree_.value

	def recurse(left, right, threshold, features, node, depth=0):
		indent = "  " * depth
		if (threshold[node] != -2):
			print indent,"if ( " + features[node] + " <= " + str(threshold[node]) + " ) {"
			if left[node] != -1:
				recurse (left, right, threshold, features, left[node], depth+1)
				print indent,"} else {"
				if right[node] != -1:
					recurse (left, right, threshold, features, right[node], depth+1)
				print indent,"}"
		else:
			print indent,"return " + str(value[node])

	recurse(left, right, threshold, features, 0)
```

dt-hacks-4.py hosted with ❤ by GitHub view raw

Let's test this function:

```
tree_to_pseudo(dt, list(iris.feature_names))
```

```
if ( petal length (cm) <= 2.45000004768 ) {
  return [[ 50.   0.   0.]]
} else {
  if ( petal width (cm) <= 1.75 ) {
    if ( petal length (cm) <= 4.94999980927 ) {
      if ( petal width (cm) <= 1.65000009537 ) {
        return [[  0.  47.   0.]]
      } else {
        return [[ 0.  0.  1.]]
      }
    } else {
```

```
        if ( petal width (cm) <= 1.54999995232 ) {
          return [[ 0.  0.  3.]]
        } else {
          if ( petal length (cm) <= 5.44999980927 ) {
            return [[ 0.  2.  0.]]
          } else {
            return [[ 0.  0.  1.]]
          }
        }
      }
    } else {
      if ( petal length (cm) <= 4.85000038147 ) {
        if ( sepal length (cm) <= 5.94999980927 ) {
          return [[ 0.  1.  0.]]
        } else {
          return [[ 0.  0.  2.]]
        }
      } else {
        return [[  0.   0.  43.]]
      }
    }
  }
```

This looks pretty good as well, and -- in my computer science-trained mind -- the use of well-placed C-style braces makes this a bit more legible then the previous attempt.

These gems have made me want to modify code to get to true decision rules, which I plan on playing with after finishing this post. If I get anywhere of note, I will return here and post my findings.

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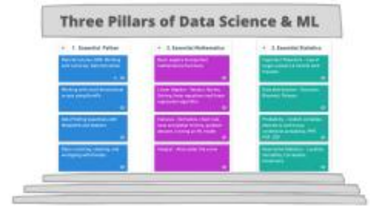

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